TEXTURE GRADIENT BASED WATERSHED SEGMENTATION

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ABSTRACT

The watershed transform is a well established tool for the segmentation of images. However, watershed segmentation is often not effective for textured regions that are perceptually homogeneous. Such regions are usually inaccurately over-segmented with no reference to any texture changes. We now introduce a novel concept of "texture gradient" implemented using a non-decimated complex wavelet transform. A novel marker location algorithm is subsequently used to locate significant homogeneous textured or non textured regions. A marker driven watershed transform is then used to properly segment the identified regions. The combined algorithm produces effective texture and intensity based segmentation for the application to content based retrieval of images.

1. INTRODUCTION

The initial stage of any watershed segmentation method is to produce a gradient image from the actual image. Within all effective schemes for obtaining gradient images (e.g. [1]) some element of smoothing is always necessary in order to emphasise the significant gradient within the image and reduce the gradient caused by noise or other minor structures.

For images containing textured regions, the necessary smoothing that is essential in gradient extraction has the effect of removing texture information. In order to improve watershed techniques and apply them properly to textured images, the texture content information that is removed should be included in the algorithm.

Texture boundaries have been used for the effective partitioning of natural images using the edge flow technique [2]. However, this technique does not use a measure of texture gradient but compares the texture content at each pixel to its neighbours in order to "flow" its texture content in the maximum gradient direction. Where "texture flows" meet, boundaries are constructed. Although effective, this method makes no use of the watershed technique. By using the watershed transform with a texture gradient we make use of the well understood theoretical basis and the large body of work associated with the watershed transform.

The use of a texture gradient for image segmentation does not also solve the main problem associated with the watershed transform: over-segmentation. There are many solutions to the problem of over-segmentation (e.g. [3, 4]). We choose to use a marker based solution (basins are flooded from selected sources rather than minima). This method lends itself well to the intended application of image region characterisation for content based retrieval. This is because the resulting boundaries will still be centred on key gradient maxima and the regions can be made to be over a minimum size.

2. TEXTURE GRADIENT

2.1. Texture Characterisation

In order to produce a texture gradient we first need to characterise the texture content of the image at each pixel. A number of methods have been proposed to do this. One of the most popular techniques is the use of a set of differently scaled and orientated complex Gabor filters [5]. By suitable spanning of the frequency space, each pixel can be characterised in texture content. However, when considering the differences in texture within an image (e.g. the texture gradient) this often produces suboptimal characterisation for the purposes of segmentation. To produce an optimal system, the Gabor filters need to be tuned to the texture content of the image. Different schemes for adaptive Gabor filtering have been implemented [6, 7]. These and other schemes use arbitrary techniques that are entirely separate from the texture feature extraction process whilst also being excessively computationally complex.

In order to integrate an adaptive scheme with the texture feature extraction process we have used the Non-Decimated Complex Wavelet Packet Transform (NDXWPT) [8]. The magnitude of the coefficients of each complex subband can be used to characterise the texture content. This is because the basis functions from each subband (very closely) resemble Gabor filters. i.e. they are scale and directionally selective whilst being frequency and spatially localised.

Each pixel can therefore be assigned a feature vector according to the magnitudes of the NDXWPT coefficients. A pixel at spatial position (x, y) has one feature for each NDXWPT subband coefficient magnitude at that position: defined as $T_i(x, y)$, where i is the subband number. A feature vector $\boldsymbol{T}(x, y)$ is therefore associated with each pixel characterising the texture content at that position.

2.2. Gradient Extraction

Figure 1(b) shows the magnitude of a single, orientated, second scale subband from a complex wavelet decomposition of the Lena test image 1(a). This image shows how the texture content is highlighted by wavelet subbands (see the feather region on Lena's hat). A naive approach to obtaining the texture gradient of an image would be to calculate the gradient of each subband magnitude and sum them. This would work for purely textured images. However, all texture extraction methods will give high energy values over simple intensity boundaries found in non-textured image regions (see the edge of the top of the hat). The gradient of the subband magnitudes will give a double edge at such intensity boundaries. The gradient of each subband should therefore aim at step detection rather than edge detection. A simple method to perform this is a separable median filtering on the magnitude image followed by gradient extraction. This has the effect of removing the edges and preserving the steps. The texture content can then be represented by the median filtered versions of the subband magnitudes $\boldsymbol{MT}(x, y)$. This can be represented by:

$$MT_i(x, y) = \text{MedianFilter}(T_i(x, y)) \text{ for } 1 < i \leq n \quad (1)$$

where n is the number of subbands and the length of the median filter is adapted to the size of the subband basis functions.

In order to calculate the gradient of the texture content one needs to consider the gradient within the multidimensional feature space. The simplest way to do this is to sum the gradients obtained for each of the individual features. Defining $TG(x, y)$ to be the magnitude of the texture gradient we have:

$$TG(x, y) = \sum_{i=1}^{n} |\nabla(MT_i(x, y))| / L_2(MT_i) \qquad (2)$$

where n is the number of subbands and ∇ is approximated using a Gaussian derivative gradient extraction technique [1]. $L_2(MT_i)$ is the L_2 norm energy of the median filtered subband i and is included to normalise the effect of each subband on the gradient.

Figure 1(c) shows an image of such a TG gradient. This clearly highlights the edge of the texture region (the feathers in the hat). Figure 1(f) shows a similar gradient image for the artificial texture montage image 1(e). Clearly this gradient is suited to the detection of texture boundaries.

In order to preserve the ability of the system to detect intensity changes, this gradient is combined with a simple intensity gradient as follows:

$$G(x, y) = mix \times \nabla f / (|\boldsymbol{MT}(x, y)|)^2 + TG(x, y) \quad (3)$$

where mix is a suitably chosen constant for mixing the intensity and texture gradients. ∇f is just the gradient of the plain intensity image calculated using an identical Gaussian derivative technique [1]. The division of the intensity gradient by the factor $(|\boldsymbol{MT}(x, y)|)^2$ was included to stop the spurious gradients inside the textures being added to the final summation. Figure 1(d) shows the gradient G for the Lena image. It clearly contains both texture and intensity boundary gradients.

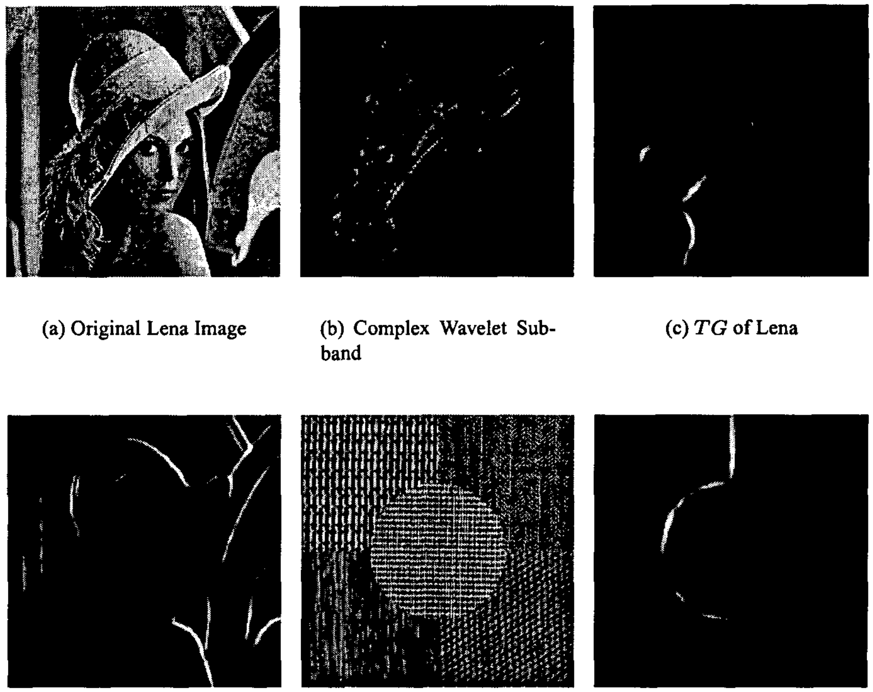
3. MARKER SELECTION

The problem of over-segmentation of the watershed method was dealt with through the flooding from selected sources (i.e. marker driven segmentation). The other methods were not chosen as they did not apply easily to texture gradients [4] or they tend to produce small residual regions (hierarchical watersheds [9]) and therefore were not suited to an application to region characterisation.

Most of the marker selection methods suggested by Beucher [3] are application dependant. The aim of marker identification within a content based retrieval application is to pinpoint regions that are homogeneous in terms of texture, colour and intensity and of a significant size. To meet these criteria a minimum region, moving threshold and region growing method was adopted as shown in Algorithm 3.1. This algorithm calculates the mean and standard deviation of the gradient image (G). Then several thresholded binary images are produced at reasonably spaced thresholds using the mean and standard deviation of G. For each binary thresholded image, the number of closed and connected regions greater than the given minimum size is calculated. The threshold with the maximum number of connected regions is used as the output marker image. This is a similar method to that developed by Deng and Manjunath [10] although this not applied to marker selection.

Consider the gradient shown in figure 1(d). If we raise and lower the threshold line by the values given in Algorithm 3.1 and keep only the contiguous areas over size 300 pixels we obtain a marker image for the maximum number of contiguous regions shown in figure 2(a). The different grayscale values within this image showing the different labelled makers. This marker image is then used to produce the segmentation shown in figure 2(b).

The governing parameter of this method is therefore the scale factor i.e. the minimum acceptable size of a marker areas (set to 300 pixels in this case).



(a) Original Lena Image (b) Complex Wavelet Subband (c) TG of Lena

(d) G for the Lena (e) Texture Montage (f) TG for 1(e)

Fig. 1. Texture gradient images

Algorithm 3.1: MINSIZETHRESHOLD($minsz, G$)

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comment: $minsz$ = the minimum acceptable marker size

comment: G = input gradient image

$std \leftarrow$ STANDARDDEVIATIONOF(G)
$mean \leftarrow$ MEANOF(G)
$threshs[12] = \{-0.9, -0.6, -0.55, -0.5, -0.4, -0.35, -0.3, -0.2, -0.1, -0.0, 0.1, 0.2\}$

for $i \leftarrow 1$ **to** 12

$$\textbf{do} \begin{cases} thresholdLevel \leftarrow mean + threshs[i] \times std \\ thresholdImage \leftarrow \mathrm{GTI}(threhsoldLevel, G) \\ markerImage[i] \leftarrow \mathrm{GCRLT}(minsz) \\ regionNumbers[i] \leftarrow \mathrm{NOR}(markerImage[i]) \end{cases}$$

$minIndex \leftarrow$ FINDMINVALUE($regionNumbers$)
return ($markerImage(minIndex)$)

comment: GTI(.)= GetThresholdImage

comment: GCRLT(.)= GetConnectedRegionsLessThan

comment: NOR(.)= Number of Regions

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4. CONCLUSION

This work introduced the concept of texture gradient and has used it to produce an effective watershed segmentation technique for natural images based on intensity and texture boundaries. Additionally, a novel marker selection algorithm has been implemented to counteract the problem of over-segmentation whilst retaining key gradient boundaries whilst giving no small residual regions.

Using this marker selection scheme with a usual image gradient will often lead to effective segmentation for non-texture images. However, the inclusion of a texture gradient based on the actual frequency content of the image (using a complex wavelet packet transform) will ensure that differently textured regions will be segmented effectively.

Traditional methods of marker extraction such as large scale low-pass filtering [3] or scale space morphological filtering [4] often move or remove salient, small scale gradient elements that can be vital for effective segmentation. Using markers extracted from the developed minimum region, moving threshold and region growing method, homogeneously textured regions can be identified. This marker extraction method uses the same gradient image as the subsequently implemented watershed transform. All small scale gradient features are therefore preserved often making a more

(a) Lena marker image (b) Segmentation of Lena (c) Segmentation of 1(e)

Fig. 2. Marker and segmentation results

effective segmentation.

Figures 2(c) and 2(b) shows the segmentation result of the Lena test image and a texture montage image (figure 1(d)) respectively. This shows the method is able to give a good general segmentation of textured and natural images.

For an entirely automatic segmentation system, the current implementation gives good results compared to other comparable techniques [2, 11]. An automatic segmentation system is important for content based retrieval applications where human interaction is impossible or unfeasible (e.g. due to the number of image or video items). It is therefore the intention to include the developed automatic segmentation techniques within a subsequently developed content based retrieval application.

Although applied solely to grayscale images, the technique could be easily generalised to colour images by averaging the resulting gradient images before using the marker extraction and watershed algorithms. Although not presently including any phase differential information in the texture gradient (as with the edge flow method), such information could be included in subsequent work as phase information is available within the complex wavelet transforms.

5. REFERENCES

[1] J. Canny, "A computational approach to edge detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 8, no. 6, pp. 269–285, November 1986.

[2] W.Y. Ma and B.S. Manjunath, "Edge flow: a framework of boundary detection and image segmentation," *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 744–749, 1997.

[3] S. Beucher and F. Meyer, "The morphological approach to segmentation: the watershed transformation," in *Mathematical Morphology and its Applications to Image Processing*, E.R. Dougherty, Ed., chapter 12, pp. 433–481. Marcel Dekker, New York, 1993.

[4] P. Jackway, "Gradient watersheds in morphological scale-space," *IEEE Transactions on Image Processing*, vol. 5, no. 6, pp. 913–921, June 1996.

[5] A.K. Jain and F. Farrokhnia, "Unsupervised texture segmentation using Gabor filters," *Pattern recognition*, vol. 23, pp. 1167–1186, 1991.

[6] W.E. Higgins T.P. Weldon and D.F. Dunn, "Gabor filter design for multiple texture segmentation," *Optical Engineering*, vol. 35, no. 10, pp. 2852–2863, October 1996.

[7] N.W. Campbell and B.T. Thomas, "Automatic selection fo Gabor Filters for Pixel Classification," *Sixth international conference on image processing and its applications*, pp. 761–765, 1997.

[8] P.R. Hill, "Enhanced Watershed Segmentation for Content Based Retrieval," *University of Bristol Technical Report TI/01-01/6*, June 2000.

[9] S. Beucher, *Segmentation d'images et morphologie mathematique*, Ph.D. thesis, School of Mines, Paris, 1990.

[10] B.S. Manjunath Y. Deng, "Colour Image Segmentation," *IEEE Conference on Computer Vision and Pattern Recognition*, vol. 2, pp. 446–451, June 1999.

[11] R. Porter, *Texture Classification and Segmentation*, Ph.D. thesis, The University of Bristol, 1997.